Biometric Data Acquisition and Monitoring via Light Signal Processing Technologies

[1*] Anna Hovakimyan, [2] Areg Oseyan, [3] Siranush Sargsyan

Yerevan State University, Armenia

**Anna Hovakimyan : ahovakimyan@ysu.am*

Information of Article

Article history:
Received:16 June 2026
Revised: 20 August 2026
Accepted: 19 September 2026
Online: 20 October 2026

Keywords:
wearable medical devices,
smart watches,
optical heart sensor,
accelerometer,
photoplethysmography,
light signal processing,
smart device software

ABSTRACT

Wearable devices enable continuous monitoring of physiological parameters through non-invasive sensors. This paper presents a biometric data acquisition and monitoring system implemented on the open-source PineTime smartwatch, designed for heart rate estimation and stress assessment using photoplethysmography (PPG) signal processing.

The system consists of two applications, HRX and Zenify. HRX provides real-time heart rate monitoring by displaying the photoplethysmographic waveform, the current heart rate estimate, and the minimum recorded heart rate. Zenify assesses stress through heart rate variability (HRV) analysis and classifies stress levels as low, moderate, or high.

The system architecture relies on PineTime's integrated HRS3300 optical heart-rate sensor (green LED, I²C interface) and BMA421 triaxial accelerometer, combined with light-signal processing algorithms implemented on the Nordic nRF52832 microcontroller. The original InfiniTime firmware was replaced with Wasp-OS, an open-source MicroPython-based watch operating system that supports rapid development and testing of biometric applications. The PPG signal is sampled at 24 Hz, a rate selected as a compromise between the higher frequencies recommended for precise HRV estimation and the power, memory, and real-time constraints of a battery-powered wearable; prior studies indicate that 20–25 Hz PPG can still provide useful heart-rate and short-term pulse-rate variability estimates in low-motion conditions. Preprocessing includes DC removal, Butterworth high- and low-pass filtering, adaptive gain control, quantization, and buffering. HRV metrics (RMSSD, SDNN, pNN50) and a Baevsky-type stress index are computed from inter-beat intervals and mapped to stress levels using thresholds informed by HRV and stress-index literature and empirical observations on the device. The controlled case study demonstrates that the emergency-alert mechanism reliably activates in simulated conditions such as absence of detectable beats, extreme heart rate, and sustained high stress, and that alerts can be propagated to a paired smartphone via Bluetooth Low Energy (BLE). Overall, the system shows that a low-cost open-source smartwatch can support transparent PPG signal processing, HRV-based stress monitoring, and proactive safety mechanisms relevant to preventive and personalized digital health.

1. Introduction

Wearable devices have revolutionized the field of personal health monitoring, enabling real-time tracking of biometric indicators. Modern smartwatches and fitness bands are equipped with optical, inertial, and wireless sensors that allow measuring not only heart rate, physical activity, and sleep patterns, but also psychological stress levels (GHAMARI & SOLTANPUR, 2018, GLASGOW INVENTIONS, 2017). These capabilities are of great importance in the field of public health and can be used within the framework of preventive medicine for such purposes as early detection of diseases, taking preventive steps, improving personal health, etc. (GHAMARI & SOLTANPUR, 2018; GLASGOW INVENTIONS, 2017).A key element of this approach is photoplethysmography (PPG). It is a non-invasive optical technique that measures blood volume fluctuations in the superficial layers of the skin, based on which it calculates heart rate (HR) and interbeat intervals (Index of Biological Integrity, IBI). IBIs can be used to calculate heart rate variability (HRV) metrics such as RMSSD, SDNN, pNN50, and other parameters related to autonomic nervous system balance and stress (KIM et al., 2018).

It should be noted that although modern wearable devices already use PPG, most of them are based on closed-source embedded software and proprietary analytics. Therefore, the development of an open-source, upgradable system for affordable devices addresses the issues of both scientific transparency and the development of digital health technologies.

Within the framework of the presented work, we designed and implemented a biometric data collection and monitoring system using light-signal processing technologies. The system

• measures heart rate and HRV in real time on the PineTime smartwatch using light signal processing,

• displays the results of these measurements to the user, including a mechanism for security warnings.

The work has practical implications from a variety of perspectives. It shows how a $25 open-source device can be combined with modern closed-source wearables, making biometric data monitoring accessible to researchers, the curious, and resource-limited environments. All steps in the processing of light signals are transparent and readily applicable to further research, academic development, and innovation. Thanks to real-time biometric feedback, the stress indicator can help track proper fitness progress, manage workload, and detect stress early. A built-in rapid response mechanism can reduce the time to get help in cardiovascular or panic emergencies.

2. Wearable Biological Monitoring Devices

In recent years, health monitoring technologies have made significant progress in both commercial products and research prototypes. The Apple Watch, Fitbit, Garmin fitness trackers, and other similar devices have made continuous heart rate monitoring available. At the same time, other technologies offer new features such as ECG (electrocardiogram) recording, blood oxygen saturation (SpO_2) measurement, and stress level assessment (GHAMARI & SOLTANPUR, 2018; SHRESTHA, 2023).

Typically, wrist-worn devices, due to their compact and convenient nature, are based on optical PPG (photoplethysmographic) sensors, while clinical devices often use electrical sensors (e.g., ECG). Although ECG is considered the gold standard for heart rate and heart rate variability measurement, numerous studies have shown that PPG technology used in wearable devices can provide sufficient accuracy under calm or controlled conditions [4]. PPG has the advantage of being easy to use and can be measured from different parts of the body (wrist, finger, earlobe). However, these devices are more sensitive to motion noise compared to chest-worn ECG sensors. In the case of stress monitoring, wearable devices use not only data from PPG sensors, but also other data such as electrical skin activity (Electrodermal activity, EDA), accelerometer readings, and skin temperature, which allow for a more complete picture of the user's physiological state and physical activity.

A systematic review published in 2024 noted that many studies have used off-the-shelf wearable devices to detect and monitor stress, including Empatica E4, Fitbit, Samsung Gear, Garmin Vivosmart, and others. In these cases, the heart rate (HR) and the heart rate variability (HRV) are the most common and widely used metrics for stress assessment (PINGE et.al., 2024). The widespread use of HR and HRV metrics stems from their close relationship with the autonomic nervous system. For example, during stress or physical exercise, an increase in HR and a decrease in HRV are commonly observed, while in a resting state, the opposite pattern is observed: a decrease in HR and an increase in HRV (BINAH.AI., 2022; KUBIOS, 2023; KE, 2023). Many algorithmic approaches for stress detection are based on this physiological phenomenon, sometimes supplemented with machine learning methods to increase accuracy. In recent years, open-source and research-oriented wearable devices have become popular, allowing developers and researchers to design and test their own biometric algorithms (Fig. 1).

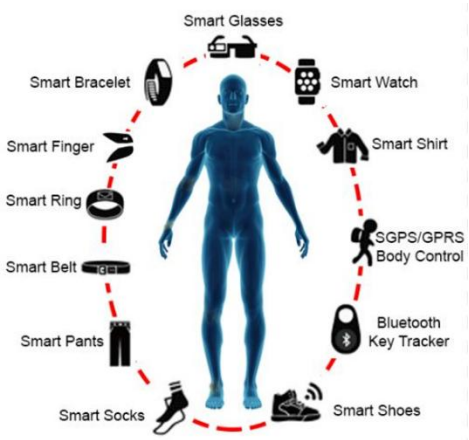

Figure 1. Biometric monitoring wearable devices

One such device is the PineTime smartwatch, created by the Pine64 organization. A similar device is Bangle.js, based on the Espruino framework. These devices allow for testing the use of new types of sensors to develop new algorithms for processing light signals, without the limitations of closed-source devices available on the market. At the same time, these devices require rigorous validation and testing to meet medical standards (PINE64 Community, 2020).

3. Principles of Photoplethysmography (PPG) and Signal Processing Methods

Photoplethysmography (PPG) is an optical measurement technique widely used in wearable devices. A PPG sensor typically consists of one or more light-emitting diodes (LEDs) that illuminate the skin and, when reflected by a receiving photodiode, record the amount of light that is either reflected or transmitted through the tissue (Fig. 2). Green light is often used to measure heart rate.

With each heartbeat, blood fills the microvasculature, which momentarily increases the blood volume in the tissue and affects the absorption of light. The PPG signal has a waveform that tracks these changes in blood volume (KIM et al., 2018; ALLEN, 2021).

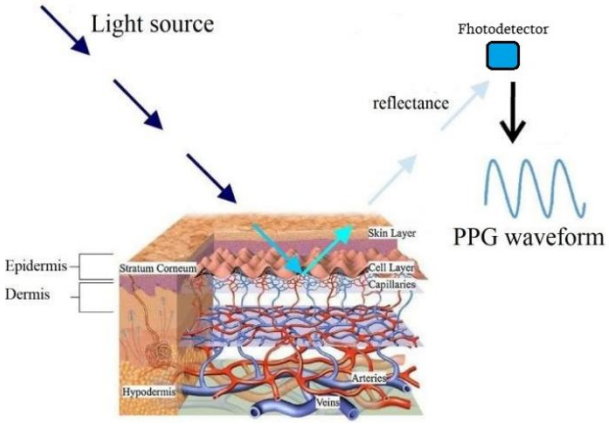

Figure 2. The mechanism of photoplethysmography (PPG)

With each heartbeat, blood fills the microvasculature, which momentarily increases the blood volume in the tissue and affects the absorption of light. The PPG signal has a waveform that tracks these changes in blood volume (KIM et al., 2018; ALLEN, 2021).

The important points on the PPG wave are the sharp rise during systole (the moment the heart contracts) and the decrease during diastole. Sometimes, secondary elements can also be observed on the PPG wave, such as a brief dip that occurs when the heart valves close.

To obtain heart rate (HR) from a PPG signal, one must be able to accurately identify the heart rate (wave peaks: maximum or minimum). In practice, this can be difficult due to noise and motion artifacts. Motion artifacts are a particularly serious problem. Wrist movements or changes in the force of contact with the sensor can cause spurious fluctuations in the optical signal (KIM et al., 2018; ALLEN, 2021).

Signal filtering and processing methods are widely used to reduce noise (KIM et al., 2018; KE et al.,,2023). One of the most commonly used filters is the band-pass filter, which extracts the expected frequency range corresponding to the heartbeat from the raw PPG signal (approximately 0.5-5 Hz or 30-300 beats/min) (KUBIOS, 2023).

The amplitude of the PPG signal can vary significantly depending on the physiological state of the user or small changes in the sensor placement. Instead of using a constant gain, which can lead to clipping if the signal is too large or too small, adaptive gain control (AGC) is used (KE et al., 2023; KUBIOS, 2023). This algorithm constantly tracks the moving peak of the signal and dynamically normalizes the signal amplitude based on it. The AGC algorithm helps to keep the PPG signal in the optimal range for analysis while rejecting sudden strong fluctuations that exceed a set threshold (KE et al., 2023; KUBIOS, 2023). PPG technology is considered a reliable method for measuring heart rate in wearable devices, but in the case of intense movements or weak contact of the sensor, the accuracy of the measurement can be significantly reduced. Regarding heart rate variability (HRV) and advanced metrics, PPG-based estimates are currently being actively studied (BINAH.AI., 2022; KE et al., 2023; KUBIOS, 2023; ALLEN, 2021). Some studies show that HRV values obtained from PPG correlate well with ECG data, especially under controlled conditions, while other studies report discrepancies, especially for certain metrics or stressful conditions (SHRESTHA, 2023).

4. Heart Rate Variability (HRV) and Stress Monitoring

Heart rate variability (HRV) quantifies the variation in the time intervals between successive heartbeats (RR intervals). Unlike the average heart rate, which summarizes the overall frequency of beats, HRV characterizes beat-to-beat dynamics and provides insight into autonomic nervous system regulation. (KIM et al., 2018; SHAFFER & GINSBERG, 2017)

Let's assume that the sequence of RR intervals includes N consecutive heartbeat intervals, $RR = (RR_1, RR_2, \dots, RR_N)$.

The mean RR interval is

$$\overline{RR} = \frac{1}{N}\sum_{n=1}^{N} RR_n$$

where RR_n is the n[th] interval of the heartbeat.

Accordingly, the average heart rate ($\overline{HR}$) will be

$$\overline{HR} = \frac{60}{\overline{RR}}$$

which gives the average heart rate in beats per minute (bpm). Since heart rate reflects the balance of the autonomic nervous system, the $\overline{RR}$ or $\overline{HR}$ are usually presented together with HRV parameter.

Several standard time-domain metrics are used to quantify HRV: (SHAFFER & GINSBERG, 2017; KUBIOS OY, 2023)

- SDNN (Standard Deviation of NN Intervals). SDNN is the standard deviation of the sequence of RR intervals over the measurement period. Here "NN" denotes normal-to-normal intervals, i.e., intervals occurring during normal sinus rhythm.

$SDNN = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}\left(RR_n - \overline{RR}\right)^2}$:

SDNN reflects overall HRV magnitude over the measurement period and contains both short- and long-term variability.

- RMSSD (Root Mean Square of Successive Differences). RMSSD is the square root of the mean squared difference between successive RR intervals and captures short-term beat-to-beat variability.

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N-1}(RR_{n+1} - RR_n)^2}$$

RMSSD is strongly associated with parasympathetic (vagal) activity and is commonly used as a short-term HRV marker (SHAFFER & GINSBERG, 2017; KUBIOS, 2023).

- **NN50** is the number of pairs of RR intervals whose difference exceeds 50 milliseconds.
- **pNN50** is the percentage of NN50 in a sequence of RR intervals.

$$pNN50 = \frac{NN50}{N-1} \times 100\%$$

NN50 and pNN50 also reflect short-term, high-frequency variability and are commonly interpreted as parasympathetic-associated markers. (SHAFFER & GINSBERG, 2017)

In healthy individuals at rest, RMSSD and pNN50 tend to be relatively high, reflecting beat-to-beat variability influenced by vagal activity and respiratory sinus arrhythmia. During acute psychological stress or physical exertion, sympathetic activation is commonly accompanied by an increase in mean heart rate and a decrease in RMSSD and pNN50. (KIM et al., 2018; SHAFFER & GINSBERG, 2017)

One widely used HRV-derived stress measure is Baevsky's Stress Index (SI), which is calculated from the distribution of RR intervals. In this paper, SI is used as a complementary indicator of rhythm rigidity and sympathetic load. (BAEVSKY, 2009)

$$SI = \frac{AMo}{2 \times Mo \times max(SDNN, 1)} \times 1000$$

where Mo is the value of the most frequently occurring interval in milliseconds (mode), AMo is the frequency of the mode in percentage format, $SDNN$ is the standard deviation of the intervals.

This metric allows to assess the level of stress based on the overall distribution of RR intervals. A high stress index (SI) indicates a situation when the heartbeats are more uniform, i.e., many intervals have the same value (mode). As a result, we have a high AMo and a low variability range. This corresponds to an overactivation of the sympathetic nervous system or a decrease in heart rate variability (HRV), i.e., a state of high stress. A low SI value indicates a wider distribution and high variability of RR intervals, which is characteristic of a calm state. In practice, the Baevsky stress index is sometimes simplified or modified.

HRV-based stress monitoring is attractive for wearable devices because cardiovascular signals can be measured passively using PPG. However, HRV is influenced by factors beyond psychological stress, including fitness level, posture, breathing pattern, and time of day. Careful context interpretation is therefore essential when classifying stress from short-term recordings. (KIM et al., 2018; PINGE et al., 2024)

5. PineTime Smart Watch

PineTime is an open-source smartwatch developed as part of the PINE64 project (Fig. 3). It is based on the Nordic nRF52832 microcontroller, which integrates an ARM Cortex-M4F processor running at 64 MHz, 512 KB of flash memory, and 64 KB of RAM, together with Bluetooth Low Energy (BLE) connectivity for wireless data transfer and communication with external devices. (PINE64 Community, 2020; PINE64 Wiki, 2021)

The main hardware components of the watch include a 1.3-inch color TFT LCD touchscreen with 240×240 pixels resolution, one multifunctional mechanical button, a vibration motor used for alerts and haptic feedback, a Bosch BMA421 triaxial accelerometer for motion and orientation sensing, and a PixArt/TianYiHeXin HRS3300 optical heart-rate sensor. The BMA421 provides 12-bit digital acceleration measurements with programmable ranges (±2 g, ±4 g, ±8 g, ±16 g) and output data rates from 8 Hz up to 1600 Hz. The HRS3300 integrates a 525 nm green LED, a photodiode, and a 14-bit ADC and provides sensor data through an I²C interface; its typical heart-rate measurement mode is about 25 Hz, which aligns with the 24 Hz rate adopted in our implementation. (NANJING TYHX ELECTRONICS CO., 2019; PINE64 Community, 2020)

Figure 3. PineTime smart watch

PineTime uses an approximately 170 mAh rechargeable battery, which is important for continuous sensor measurements and background BLE connectivity. The hardware schematics and pin mapping are openly documented, enabling direct access to raw sensor data and configuration of operating parameters from custom firmware. (PINE64. 2019; PINE64 Community, 2020)

One of the main advantages of PineTime is that it is designed to work with open-source embedded software such as InfiniTime and Wasp-OS. This design philosophy makes it possible to communicate directly with the PPG and accelerometer sensors, adjust their operating modes, and implement custom biometric algorithms without the limitations of closed-source commercial wearables. (PINE64 Wiki, 2021; THOMPSON, 2020)

6. System Architecture

The developed system includes the HRX and Zenify applications, whose architecture supports the flow from sensor data acquisition to user display and alerting. HRX is intended for continuous heart-rate monitoring during daily activity or exercise, while Zenify focuses on short-term stress assessment during rest or periodic self-checks.

The architecture can be logically divided into the following layers:

Sensors. PineTime's HRS3300 heart-rate sensor (PPG) and BMA421 accelerometer provide raw input data. The PPG sensor outputs light-intensity samples related to blood volume changes, whereas the accelerometer provides motion and posture information. (NANJING TYHX ELECTRONICS CO., 2019; PINE64 Community, 2020)

Data Acquisition Layer. Wasp-OS device drivers configure the heart-rate sensor and accelerometer and read data at specified frequencies. For HRX and Zenify, the HRS3300 PPG channel is sampled at an effective rate of 24 Hz by scheduling three sensor readings within each 8 Hz system tick.

Signal Processing Layer. Raw PPG samples undergo preprocessing, including DC removal, high-pass and low-pass Butterworth filtering, adaptive gain control, and quantization, to obtain a stable waveform suitable for peak detection and HR/HRV analysis. (KE et al., 2023; KUBIOS OY, 2023)

Algorithmic Analysis. Depending on the active application, the processed PPG signal is used either to estimate heart rate via autocorrelation (HRX) or to compute RR intervals and HRV metrics (RMSSD, SDNN, pNN50) and the Baevsky stress index (Zenify). (SHAFFER & GINSBERG, 2017; BAEVSKY, 2009)

User Interface. The HRX interface displays a scrolling PPG waveform, the current heart-rate value, and the minimum heart rate observed during the session. The Zenify interface displays the PPG waveform, the RMSSD value converted to milliseconds, and a color-coded stress level indicator ("Low", "Medium", "High").

Alerts and Notifications. If certain safety conditions are met (absence of detectable beats, extreme heart rate at rest, or sustained high stress), the watch triggers on-device visual and haptic warnings and can send BLE notifications to a paired smartphone for further action, such as forwarding an emergency message.

The system architecture is represented as a workflow diagram (Fig. 4), which summarizes the main processing stages from sensor acquisition to application-level outputs.

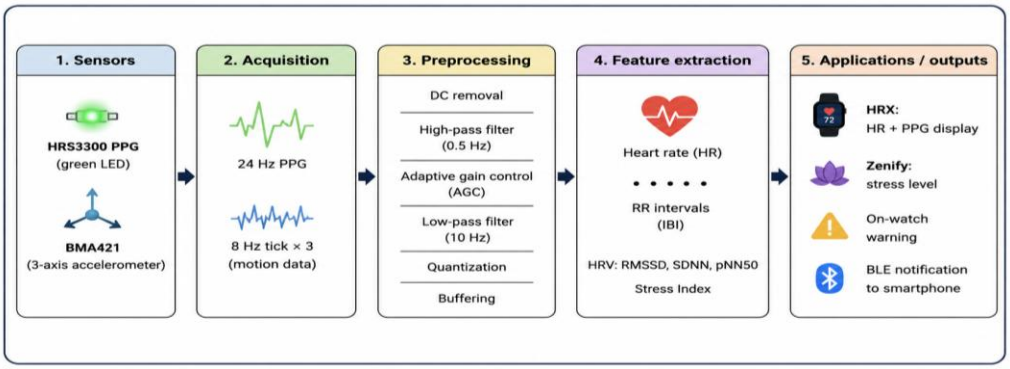

Figure 4. System workflow from sensor acquisition to output

The diagram shows: (1,2) PPG and accelerometer data acquisition, (3) PPG preprocessing (DC removal, band-pass filtering, adaptive gain control, quantization), (4) feature extraction (RR intervals, HR, HRV metrics, stress index), and (5) application-level outputs (HRX heart-rate display; Zenify stress-level classification and alerts).

7. PPG Signal Processing in HRX App

Converting raw measurements from a PPG sensor into a stable and reliable heart rate signal is a non-trivial task. We have developed an algorithm based on well-known PPG signal processing methods. (PINGE, 2024; KUBIOS, 2023) The developed algorithm includes the following steps.

1. ***Initialization.*** At application startup, an initial measurement is taken from the PPG sensor to estimate the baseline offset. This value approximates the DC component (Direct Current component) of the signal, which reflects ambient light and the average optical properties of the tissue. It is then used during signal preprocessing.
2. ***Periodic Sampling.*** A timer is set to take readings from the sensor approximately 24 times per second (24Hz). This is done by programming sub-ticks in the Wasp-OS tick manager. The digital value of the signal received from the sensor is proportional to the intensity of the reflected light.
3. ***Measurement Preprocessing***. The following steps are performed for each raw measurement value x_n.
    - ***DC component removal.*** $y_n = x_n - offset$ is calculated. This step centers the signal around zero. The baseline offset is not reevaluated for each measurement over time, but it can be gradually updated to compensate for slow signal drift.

- ***High-Pass Filter (HPF).*** The signal $y_n$is passed through a high-pass filter to remove very low-frequency components, such as slow changes due to blood volume fluctuations or sensor movement. We used a second-order Butterworth high-pass filter with a cutoff frequency of approximately 0.5 Hz, which preserves the rapid oscillations characteristic of heartbeats. (KUBIOS, 2023; ALLEN, 2021)
- ***Adaptive Gain Control (AGC).*** An adaptive gain control is implemented that monitors the signal amplitude and dynamically adjusts it. AGC performs two main functions:
  - suppresses sudden large fluctuations by removing all values that exceed a threshold set for the moving peak estimate of the waveform,
  - strengthens signals with low intensity, ensuring the use of the entire dynamic range.

This approach provides normalization of the signal amplitude, neutralizing the effect of sensor contact or position changes. (KUBIOS, 2023; ALLEN, 2021)

- ***Low-Pass Filter (LPF).*** The signal is passed through a low-pass filter to smooth out high-frequency noise. We used a second-order filter with a cutoff frequency of approximately 10 Hz. The result is a pulse signal that is mostly consistent with the heartbeat (KUBIOS, 2023; ALLEN, 2021).
- ***Quantization.*** The processed value is converted to an integer p_n.
- ***Buffering.*** p_n is added to a circular buffer that stores the last few seconds of data for heart rate calculation.

Table 1. PPG preprocessing filter configuration

Component	Type	Order	Cutoff / Passband	Sampling frequency	Rationale
DC removal	Baseline subtraction	–	–	24 Hz	Removes static offset due to ambient light and tissue properties.
High-pass filter (HPF)	Butterworth IIR	2	0.5 Hz	24 Hz	Suppresses slow baseline drift and very low-frequency components.
Adaptive gain control	Peak-tracking AGC	–	Threshold based on moving peak estimate	24 Hz	Normalizes amplitude and rejects outlier spikes from motion.
Low-pass filter (LPF)	Butterworth IIR	2	10 Hz	24 Hz	Attenuates high-frequency sensor noise while preserving the cardiac band.
Band-pass effect	HPF + LPF combined	–	Approx. 0.5–10 Hz	24 Hz	Captures the fundamental and lower harmonics of the heart-rate signal (≈30–300

Component	Type	Order	Cutoff / Passband	Sampling frequency	Rationale
					bpm).

The chosen band-pass (approximately 0.5–10 Hz) follows common practice for wearable PPG heart-rate extraction and balances noise suppression with preservation of relevant pulse morphology. (KE et al., 2023; KUBIOS OY, 2023)

Sampling Frequency Considerations

The PPG sampling frequency was set to 24 Hz by scheduling three sensor readings during each 8 Hz Wasp-OS application tick, which is close to the typical 25 Hz heart-rate sampling mode specified for the HRS3300. (NANJING TYHX ELECTRONICS CO., 2019) Although higher sampling frequencies can improve the precision of HRV metrics, time-domain pulse-rate variability can still be estimated at approximately 20–25 Hz for short-term monitoring under low-motion conditions. (KE et al., 2023; PINGE et al., 2024) In our design, 24 Hz was selected as a compromise between algorithmic accuracy, CPU load on the nRF52832 microcontroller, battery life, and memory requirements for on-device buffering.

4. ***Heart Rate Calculation***. Heart rate is calculated when enough preprocessed data p_n is accumulated to reliably detect the periodicity of the waveform. In practice, several approaches are used:
    - ***Peak Detection in Time Domain.*** A common approach is to detect peaks or dips corresponding to heartbeats in the p_n time series, measure the RR intervals between them, and calculate the heart rate. This method is used in Zenify's HRV module. In the HRX application, where direct HRdisplaying is required, we have used an alternative method based on autocorrelation.
    - ***Autocorrelation Approach.*** In the HRX application, we have used an algorithm that is close to autocorrelation. This method consists of "sliding" the copy of the last received PPG wave onto itself with different "lags" and calculating at which lag the wave most closely matches its own copy, i.e., has the smallest mean squared difference. This search is performed over a probable range that corresponds to a heart rate of approximately 30 to 210 beats per minute (BPM). When the lag N_{lag}, corresponding to the main period, is found, the BPM is calculated.

$$BPM = \frac{60 \times f_s}{N_{lag}}$$

where f_s is the sampling frequency, i.e., the number of measurements taken per second, N_{lag} is the detected lag, which corresponds to the interval of one heartbeat.

After the main interval is detected, the result is refined by checking multiples of that deviation (2x, 3x...) to ensure that the detected interval is truly a heartbeat interval, and not a spurious match caused by noise. If a reliable interval cannot be detected due to noise or insufficient data, the algorithm does not return a heart rate value. In our implementation, we wait at least 8-10 seconds for data accumulation (approximately 200+ samples) before performing the first stable calculation.

5. ***Continuous Update.*** In the HRX app, the calculated heart rate is immediately displayed on the screen, after which the data buffer is cleared for the accumulation of new measurements and the next calculation. The PPG wave graph on the screen is updated approximately every 125 milliseconds, and the digital BPM value is updated approximately every 5-10 seconds.

8. HRV Analysis in the Zenify App

In the Zenify app, unlike HRX, the data buffer is not cleared after the calculation. Instead, a circular buffer is maintained for data collected over a fixed period of time. For example, a 12-second coverage period corresponds to approximately 288 samples at 24 Hz. A peak-detection algorithm is continuously run on this buffer. A sample is

considered a peak if it is higher than its two adjacent values, has a minimum amplitude, and is at least 0.5 seconds away from the previously detected peak. The index of each detected peak is recorded, and the distances between successive peaks are converted using the 24 Hz sampling frequency to obtain RR intervals in milliseconds. Based on these intervals, HR, RMSSD, SDNN, pNN50, and the Baevsky Stress Index (SI) are calculated once per second after the initial data-accumulation phase.

Stress-Level Classification in Zenify

The classification thresholds were selected in two steps. First, we consulted normative HRV and Baevsky stress-index literature, which reports typical resting SI values around 80–150 units and indicates that substantially higher values can be associated with increased sympathetic load. (BAEVSKY, 2009; KIM et al., 2018) Second, we analyzed our own recordings from calm and stressed states, including post-exercise and self-reported high-tension episodes, to identify ranges of RMSSD and SI that consistently differentiated these conditions on PineTime.

In the current implementation:

Low stress is assigned when RMSSD exceeds a conservative parasympathetic threshold (for example, >20–30 ms for the short window used in Zenify) and SI remains in a normal or low range (for example, <400), indicating higher variability and lower sympathetic strain. (SHAFFER & GINSBERG, 2017; BAEVSKY, 2009)

Medium stress is assigned when metrics fall in intermediate ranges (for example, SI between approximately 400 and 800 and RMSSD near or slightly below the resting threshold), suggesting noticeable activation but not extreme strain.

High stress is assigned when RMSSD is very low (for example, <20 ms in our short-term recordings) or SI is very high (for example, >800), reflecting a markedly rigid rhythm and dominant sympathetic activity.

These numerical thresholds are not intended as clinical cut-offs but as device-specific operating points for classifying short-term HRV patterns recorded by PineTime under everyday conditions. As an additional safeguard, Zenify suppresses updates when too few peaks are detected or when accelerometer data indicate strong motion, thereby avoiding unreliable stress estimates from noisy signals.

The algorithms run on the nRF52832 microcontroller within the constraints of the MicroPython environment. The amount of data processed in each update is small enough for real-time operation on the device.

The overall processing chain is transparent and explainable, with each step having an identifiable signal-processing or physiological basis.

9. Responding to Emergencies

The developed system also includes a mechanism for detecting emergency situations and responding to them in real time. Since the PineTime watch does not have cellular connectivity, it is assumed that the watch is connected to a smartphone via Bluetooth Low Energy (BLE) to transmit signals.

The logic of the alert mechanism is built around the following sequential steps.

- **Emergency detection**

The system constantly monitors situations that may indicate a biological threat.

- ***No heartbeat***. If the PPG waveform is flat or no peaks are detected for 10 seconds, this may indicate either a loss of connection to the watch or the absence of a pulse from the user. This situation is considered a potential danger. However, the lack of a signal is often due to the watch being removed from the wrist or moving, so the system additionally checks for movement based on accelerometer data to exclude the possibility of false alarms.
- ***Extreme heart rate***. If the resting heart rate exceeds 180 beats/min or falls below 30 beats/min and persists for a certain period of time, the system also considers it a critical situation.

- ***High stress and lack of response*.** If the stress level remains “High” for a long time and the user does not respond, it may be an indication of poor well-being.
- ***Fall detection*** (future integration planned). The accelerometer will be able to detect sudden falls and immobility, which, together with heart data, can indicate possible fainting or cardiac arrest.

- **User alert mechanism**

If a danger is detected, the watch first attempts to alert the user on the spot.

- By displaying a bright warning message on the screen, for example, “Abnormal heart rhythm!”,
- By activating the vibrator in a specific alert style,
- The user can cancel the alert, for example, by touching the screen or pressing a physical button,
- A time limit is provided for receiving a response, for example, 30 seconds.

- **Turning into an emergency**

If the user does not respond, the watch sends a signal to the smartphone via BLE connection through the appropriate application. Upon receiving the signal, the smartphone can:

- Send an SMS to a designated emergency contact, including the user's last location,
- Make an automatic call,
- In a well-integrated system, call the emergency services and transfer the message.

- **Insurance against false alarms**

The response mechanisms are designed in such a way that a potential threat is confirmed by multiple measurements, after which they are activated, reducing the likelihood of false alarms and unnecessary emergency responses. An important stage here is the user's warning.

- **Integration into applications**

Verification mechanisms are built into the core workflow of HRX and Zenify applications.

- In the HRX app, if no heart rate is calculated after a certain period of time and the PPG waveform is almost flat, an internal warning system is activated.
- In the Zenify app, if the stress level remains “high” for several consecutive updates and, possibly, the heart rate exceeds a set threshold, the app activates a warning, suggesting the user relax or confirm that everything is fine. It is also possible to implement a special "Panic Button", which, when pressed for a long time, allows the user to manually send an SOS signal.

10. User Interface

After installing the new firmware, the HRX and ZENIFY applications become available in the PineTime application launcher, alongside the other built-in applications. Fig. 5 shows the application launcher, where the Zenify application icon is also visible.

Figure 5. PineTime's applications window

When the user selects an app, the watch opens the app's launcher. Both apps use a black background with colored text and graphics, providing better readability on a small screen.

Heart Rate Monitoring App (HRX)

After launching the HRX app, the text “HR Graph” is initially displayed, and after a few seconds, the PPG waveform corresponding to the heartbeat begins to appear on the screen in blue. After accumulating data for approximately 10 seconds, the heart rate indicator appears at the top of the screen: 64 bpm (Fig. 6).

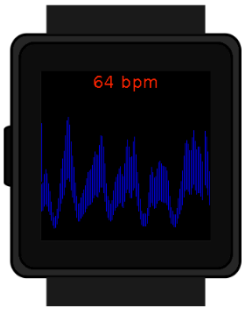

Figure 6. Heart rate and PPG waveform graph

Each peak on the PPG waveform graph represents one heartbeat. The value "64 bpm" displayed at the top represents the currently calculated heart rate. This value is updated after each new calculation, approximately every 10 seconds, but more frequent updates are possible if the algorithm detects a stable beat sequence earlier. The graph dynamically moves from right to left, providing a continuous view. The heart rate is recorded during the given measurement (Fig. 7).

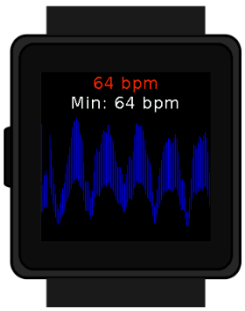

Figure 7. Current and minimum heart rate (64 beats/minute)

In the presented case, the minimum value coincides with the current one, which means that the heart rate did not drop below 64 during the measurement.

Stress Monitoring App (Zenify)

When you launch the Zenify app, the word "PPG" and a scaled HR graph appear at the top of the screen (Fig. 8).

Figure 8. Zenify app home screen

After about 5-6 seconds, the word "PPG" is replaced by the text "Stress: [Level]", and the RMSSD value is displayed below it (Fig. 9).

Figure 9. Stress level was assessed as low

The color shaping of stress levels (green, orange, red) allows the user to get a quick and clear visual perception.

An RMSSD value of 1012 corresponds to approximately 42 milliseconds (1012/24≈42.2) at a device sampling rate of 24 Hz, which is usual typical of a quiescent state and corresponds to a "Stress: Low" rating. When this value falls below 20ms, the app rates stress as “medium” or “high.” Note that the PPG signal graph continues to be displayed throughout the sampling period, providing a continuous view of physiological activity.

During testing, when the user performed a short physical exercise, for example, 15 jumps, and then launched the Zenify application, the message “Stress: High” appeared on the screen, and the RMSSD indicator was in the range of approximately 10-15 milliseconds. As a result of just a few minutes of deep breathing, the application first recorded a decrease in stress levels to “medium”, then to “low”, which was accompanied by an increase in RMSSD and stabilization of the heart rate.

11. Case Study: Emergency-Alert Functionality

The emergency-alert mechanism was evaluated in a controlled setting using both real PPG recordings and synthetic data streams to emulate different risk scenarios. Since PineTime does not have cellular connectivity, the design assumes that the watch is paired with a smartphone via BLE for forwarding alerts.

1. Loss of detectable heartbeat. The PPG waveform was artificially flattened or replaced by a constant value to emulate either removal of the watch from the wrist or a potential cardiac arrest. In these tests, the system detected the absence of peaks within approximately 10 seconds, triggered a strong vibration and on-screen warning (“No heartbeat – Are you okay?”), and, if the user did not respond within a specified time window (for example, 30 seconds), sent a BLE notification to the paired smartphone.

2. Extreme heart rate at rest. Using either accelerated synthetic PPG waveforms or recordings taken shortly after intense activity, we simulated cases where heart rate exceeded a critical upper threshold (for example, >180 bpm) or dropped below a very low threshold (for example, <30 bpm) for a sustained period. When such conditions persisted beyond the configured minimum duration, the watch displayed an alert (“Abnormal heart rhythm!”) and activated haptic feedback; the smartphone subsequently received an alert message via BLE.

3. Sustained high stress without user acknowledgement. By inducing short bursts of physical exercise and cognitive load followed by rest, we generated sequences where Zenify repeatedly classified stress as “High” while mean heart rate remained elevated. In these situations, the app prompted the user to relax or confirm well-being; if no interaction occurred over several consecutive updates, the system escalated to an emergency warning, with behavior similar to the extreme-heart-rate scenario.

Across these controlled simulations, the emergency pipeline (watch warning → user interaction window → BLE notification) behaved as intended, and the smartphone application successfully logged the corresponding alerts. Because the tests relied on a limited number of synthetic and semi-controlled scenarios and did not involve real medical emergencies, we do not report formal sensitivity, specificity, or false-alarm rates; these will require larger-scale validation with clinical or field data. Nevertheless, the case study confirms that the implemented logic can

detect several classes of potentially dangerous patterns and initiate a multi-step response that escalates from local feedback to remote notification when the user fails to respond.

12. Conclusion

This project is a good example of how an open-source smartwatch (PineTime) can be turned into an effective biometric monitoring tool based on PPG signal processing. We managed to implement continuous heart rate monitoring and real-time stress assessment on a device that is significantly more affordable than other similar smartwatches. Another important result is that algorithms and methods (filtering, HRV calculation, etc.) that are typically used in clinical or specialized devices can be efficiently implemented on resource-constrained hardware with sufficient accuracy. This highlights the effective use of open hardware solutions in healthcare technologies, demonstrating that it is not necessary to use expensive dedicated systems to provide access to biometric indicators.

The system not only measures heart rate but also calculates heart rate variability (HRV) indicators, based on which it assesses stress levels. The stress assessments obtained by the Zenify app largely corresponded to both expected physiological and subjective states. This confirms the applicability of HRV in wearable devices as a non-invasive stress assessment tool. Another important innovation was the integration of a safety mechanism. Although the mechanism was relatively simple, the fact that a $25 watch could detect a dangerous health condition and trigger an appropriate response chain says a lot about the system's capabilities. This is a great example of how, with further improvements, open-source wearables could help detect fainting or heart attacks in vulnerable populations.

The system also highlights the advantages of using Wasp-OS and MicroPython for rapid development of such applications. The transition from InfiniTime to Wasp-OS was justified, taking into account the high speed of software module development and testing. This work may also inspire other researchers to use MicroPython for the development and testing of experimental projects on PineTime or similar devices.

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